A New Methodology to Improve Myoelectric Signal Processing Using Handwriting

Moussa Djoua  Réjean Plamondon
Département de Génie Électrique, Laboratoire Scribens, École Polytechnique de Montréal, C.P. 6079, Station Centre-Ville Montréal QC Canada, H3C 3A7
moussa.djioua@polymtl.ca  rejean.plamondon@polymtl.ca

Abstract

In this paper, a new biomedical application of handwriting is proposed to enhance the processing of surface electromyographic (SEMG) signals by using the Delta-Lognormal model of the Kinematic Theory of rapid human movements. Three applications are developed from this model: the first two exploit specific time indexes of the end-effector velocity profiles, as recorded by a digitizer. These indexes are used 1) to circumscribe the portions of SEMG corresponding to the duration of the rapid movement and 2) to enhance the shape of the SEMG envelopes, constructed from a sum of trials collected during repetitive motor tasks. The third application, which does not exploit any kinematic information of the end-effector, aims at decoding the time plan of the muscle activities. Such a plan is assumed to be used in the motor control of smooth complex movements. The resulting tool provides new insights that could be exploited, for example, in the recognition from SEMG envelopes of specific patterns from which artificial commands could be constructed to control prosthesis or exoskeleton movements.

Keywords: Handwriting, SEMG, Kinematic Theory, Delta-Lognormal model, bio-medical signal processing.

1. Introduction

Handwriting requires a high level of dexterity. Its motor control can be observed in a noninvasive way through various signals from the X-Y trajectory of a hand moving a pen on a digitizer to surface electromyographic signals (SEMG) recorded on some upper limb muscles. These bio-signals are exploited in various applications. In psychophysical experiences dealing with single rapid strokes, the analysis seeks to calculate the movement starting time and its duration by simultaneously using SEMG and kinematic signals [1],[11],[18]. In the case of complex movements, one rather looks for portions of the SEMG patterns that correspond to elementary sub-movements. In such projects, time and frequency based characteristics of the SEMG are used [25],[31],[32].

The time-based information embedded in these bio-signals is, for examples, extracted to analyze indirectly the intrinsic behavior of the neuromuscular systems and correlated with the health status of human subjects, or to synthesize specific signals to control prosthesis or exoskeletons [9],[15],[17],[27]. On the one hand, handwriting kinematics becomes an easy and noninvasive tool in the diagnosis process of neuromuscular diseases. Specially, single strokes, considered as a primitive of handwriting [16],[33],[36],[37], are analyzed to characterize neurodegenerative processes like Parkinson’s and Alzheimer’s disease [30],[34]. They are also used as key patterns to evaluate the recovery processes in the rehabilitation of patients from cerebrovascular accidents [26]. On the other hand, the analysis of SEMG signals is an important technique for a variety of applications dealing with neurological diagnosis, sport medicine, prosthetics, rehabilitation, etc. For example, research in neuroscience has been put at contribution to study the possibility of accurately controlling anthropomorphic robot systems with neuronal and neuromuscular signals by generating suitable commands to control the various actuators that reproduce skilled human movements such as a handwriting [3],[10],[19],[28],[35],[38].

In this study, we propose a novel contribution dealing with the use of handwriting as a tool for SEMG signal processing. Three techniques (or applications) are investigated, adapted from the analysis by synthesis of handwriting with the Kinematic Theory of rapid human movements [22-24]. The first technique aims to identify the SEMG portion corresponding to a rapid movement. The second allows the improvement of the SEMG envelope computed from the superimposition of a set of trials, recorded during the repetitive execution of strokes. The third one is developed to circumscribe the onset and the termination of individual muscle activation in complex movements, which leads to the decoding of the time-plan of muscle recruitments adopted for motor control. The first two techniques uses the kinematic information extracted
from the recorded end-effector trajectories, while the third technique uses only myoelectric information to model the SEMG envelopes by a sum of lognormal shapes.

The remainder of this paper is structured as follows: The Delta-Lognormal model, kernel of the Kinematic Theory, is overviewed in section 2. In section 3, the psychophysical reaction time protocol used to study rapid movements is introduced and exploited to implement the two first techniques. Section 4 presents the third application, a typical method to estimate from SEMG, the time plan of muscle contractions during complex movements.

2. Overview of the Delta-Lognormal model

The Delta-Lognormal model has been developed in the context of the analysis and synthesis of handwriting [23], [24]. It describes the velocity profile \( v(t) \) of a rapid movement by a difference of two lognormal components which respectively represent the impulse responses of an agonist and antagonist neuromuscular systems, weighted by their respective commands \( D_1 \) and \( D_2 \), synchronously activated at time \( t_0 \). When the agonist and the antagonist components of the velocity are in perfect opposition, \( v(t) \) is modeled by a Delta-Lognormal equation:

\[
v(t) = D_1 \Lambda(t; t_0, \mu_1, \sigma_1^2) - D_2 \Lambda(t; t_0, \mu_2, \sigma_2^2) \tag{1}
\]

where

\[
\Lambda(t; t_0, \mu, \sigma) = \begin{cases} 
\frac{1}{\sigma \sqrt{2\pi}} \exp \left[ -\frac{1}{2} \left( \frac{\ln(t - t_0) - \mu}{\sigma} \right)^2 \right] & \text{for } t_0 < t \\
0 & \text{elsewhere}
\end{cases}
\tag{2}
\]

and \( D_1, D_2 \) being the respective amplitudes of the input commands, \( t_0 \) the time occurrence of these input commands, and \( \mu \) and \( \sigma \) the logtime delay and the logresponse time of the neuromuscular systems respectively, as expressed on a logarithmic time scale. The description of a velocity profile according to (1) requires seven parameters, three of them acting as the motor commands \( (t_0, D_1, D_2) \) and the other four characterizing the timing properties of the two neuromuscular systems \( (\mu_1, \sigma_1, \mu_2, \sigma_2) \) responding to these commands.

Other time indexes are often used to characterize a rapid movement particularly, the time onset \( t_{onset} \) that represents a time index when the movement becomes significant and the movement time \( (MT) \) that corresponds to the effective duration of the entire trajectory (see Fig.1). Usually, these two time marks are measured from dynamic (force or pressure) and kinematic (velocity) signals, using empirical or statistical thresholds [14]. Instead of these methods, the Kinematic Theory avoids subjective thresholds and yields to an analytical approach for the estimation of these indexes. Indeed, according to the properties of a lognormal, 99.97 % of the distance covered by the agonist or the antagonist component is included in the following interval

\[
I = \left[ e^{\mu - 3\sigma}, e^{\mu + 3\sigma} \right]
\tag{3}
\]

And, in the case of the Delta-Lognormal model, \( t_{onset} \) corresponds to the time index when 0.03 % of the distance is covered and \( MT \) corresponds to the duration where 99.97 % of the total distance is passed through. Their formal definitions are respectively given by (see Fig.1):

\[
t_{onset} = t_0 + \min \left\{ e^{\mu_1 - 3\sigma_1}, e^{\mu_2 - 3\sigma_2} \right\},
\tag{4}
\]

\[
MT = \max \left\{ e^{\mu_1 + 3\sigma_1}, e^{\mu_2 + 3\sigma_2} \right\} - \min \left\{ e^{\mu_1 - 3\sigma_1}, e^{\mu_2 - 3\sigma_2} \right\}.
\tag{5}
\]

Thus, the seven parameters of the Delta-Lognormal model lead to the construction of time references which allow the identification of various and distinct phases of the movement genesis, such as the perception/preparation and execution phases. As one can distinguish in Fig.1, the time occurrence \( t_0 \) represents the time onset of the neuromotor command and \( t_{onset} \), the time onset of the effective movement.

3. Applications in psychophysical experiments

One of the basic and simplest psychophysical experiments is to measure reaction times of subjects, prompted by external stimuli to execute simple motor tasks, such as pushing buttons or making rapid point-to-point movements. Various bio-signals (dynamic, kinematic, SEMG, EEG, etc.) are then recorded and treated to estimate the time required by the subjects to react to the stimulus. With the

Figure 1. Representation of the velocity profile of a rapid movement by a Delta-Lognormal function. The movement onset \( t_{onset} \) and duration \( MT \) are also indicated.
Delta-lognormal model the previously defined time indexes can also be computed on top of the reaction time information. Fig. 2 describes a movement and its associated time–indexes as extracted from its velocity profile. Practically, a visual or an audio stimulus (a Go signal) is randomly generated by a stimulator. Some processes occur before the startup of the end-effector move. The Central Nervous System (CNS) decodes and identifies the nature of the stimulus and sends suitable commands to carry out the required motor tasks. The movement genesis is thus made up of three main phases: stimulus perception/command preparation, neuromuscular command instantiation/propagation and movement execution [21]. According to the Delta-lognormal model, three main time–indexes can be used to circumscribe such a movement: the time–origin \( t = 0 \), the time occurrence \( t \), and the movement onset \( t_{\text{onset}} \). The first index \( t = 0 \) is fixed by the stimulus generator; the last index is usually assimilated to the reaction time and calculated using an empirical threshold. In our method it is computed using equation (4). The command onset \( t \), which is not measured in classical experiments provides a way to split the reaction time period into the first two phases.

### Figure 3. Illustration of the experimental set-up

3.1. **Technique 1: Estimation of the time indexes**

This first technique aims at processing individual SEMG signals. It consists in isolating a portion of the SEMG that reflects the effective activity of a muscle involved in the production of a rapid movement. The method simultaneously uses the kinematic and the SEMG biosignals. Fig.4.a depicts an original SEMG recorded at the flexor digitori profundus muscle (a muscle located in the forearm which flexes the fingers) during a rapid hand movement [7]. After rectification (Fig. 4.b), its envelope is calculated using a Savitzky-Golay filter [29] with a smooth window width of 100 ms (Fig.4.c). Fig. 4.d depicts the corresponding velocity profile of the end-effector. The effective SEMG activity, delimited by a dashed rectangle in Fig. 3.c, can be isolated using equations (4) and (5) and
the Delta-Lognormal parameters extracted from the velocity profile with a parameter extraction software [6],[20].

3.2. Technique 2: Synchronization of SEMG superposition

This second technique deals with a processing of a set SEMG recorded during the repetitive execution of the same motor task. Indeed, a basic technique used in this kind of experiments consists in computing the envelope of the electromyographic signals from a sum of trials collected during a repetitive experiment.

Thus, the main activity is amplified while the random activities vanish, the signal to noise ratio increases and specific bell-shaped patterns emerge in the mean envelope. The main problem for summing up the all trials is the choice of the time reference. Classically, this time corresponds to the appearance of the stimulus \( t = 0 \). However, according to the Kinematic Theory, each individual movement is initiated at \( t_0 \) (see Fig. 2) and this parameter must be used as the time reference, instead of \( t = 0 \), to process the SEMG envelope. This removes the effect of the perception phase which varies from trial to trial, and desynchronizes the superimposition. Fig. 5 illustrates this point with a SEMG envelope calculated from a set of thirty trials recorded on the digitorum profundus flexor muscle when a human subject repeats a rapid movement [7]. Fig.5.a displays the classical SEMG superimposition when the stimulus onset is used as time origin; Fig. 5.b highlights the improvements that results when, for each trial, the corresponding \( t_0 \) is used as the time origin of the summation. In Fig. 5.c the differences between the envelopes depicted in Fig. 5a and 5b is plotted. As one can see, by using \( t_0 \) in the SEMG superimposition as a time reference, most of the ripples vanish, leading to a single slightly asymmetric bell-shaped profile, which can be modeled by analytical expressions [7],[12],[13].

![Figure 4](image-url) Figure.4. Movement analysis through SEMG and kinematic signals a) Original SEMG of a flexor muscle b) its rectified waveform c) its corresponding envelope and d) the velocity profile of the end-effector. The circumscription of the muscle activity is done by using \( t_{onset} \) and \( MT \), as calculated with the Delta-Lognormal parameters.

![Figure 5](image-url) Figure.5. Typical example of SEMG envelope calculated by using different time references for the superimposition. (a) classical result which uses \( t = 0 \) as a time reference. The arrow represents \( \bar{t}_0 \) the mean time occurrence of the neuromotor commands, as calculated from the velocity trials. (b) result from our new technique which uses \( t_0 \) as a time reference for each individual trial (c) Comparison between a and b, after time shifting a with \( \bar{t}_0 \), to highlight the ripple reduction improvement obtained with our new technique.

3.3. Technique 3: Construction of a time plan for muscle activation

The third technique, which deals only with surface myoelectric signals, aims at modeling SEMG envelopes by the superimposition of bursts; having lognormal shapes. Each burst corresponds to the electrical activity of muscle contraction for the execution of an elementary motor task, contributing in the generation of a stroke by the end-
effector. The stroke itself is considered as a primitive from which complex handwriting patterns are build by vectorial superimposition [4] [5]. In this case, the mathematical background of the Kinematic Theory concerning the superposition of lognormal functions is exploited to model SEMG envelopes and extract time indexes which lead to the decoding of the time-plan of muscle recruitment. Indeed, to generate complex movements like handwriting, the contraction of the different upper limb muscles is done according to a specific recruitment time plan which results in the smooth trajectory of the pen grasped by a hand. This coordination, performed at the CNS level, reflects the motor control of skilled movements. For a single stroke, the recruitment and thereby the contraction of each muscle appears in the phasic SEMG component as a burst which can be described on a time scale by its onset and duration. For a complex movement, one observes a superposition of successive bursts. So far, the envelope of each burst has been modeled by various bell-shaped profiles such as gaussian functions [12]. Among other things, this modeling aims at improving the use of SEMG bio-signals in the construction of artificial intelligent systems dedicated for the control of prosthesis [3],[35].

However, to take into account the asymmetric waveform of this profile, a lognormal function is a more adapted pattern [7] and one can thus model the SEMG envelopes of muscles recruited in the generation of handwriting by a sum of lognormals. The time plan employed by the CNS to control such movements can then be decoded by estimating the time onset and the duration of each muscle contraction after extracting the lognormal parameters of the sequence.

**Figure.6** Typical example of a complex oscillating handwritten trajectory.

Fig.7 highlights the use of this methodology to estimate the successive contractions of the digitorum profundus flexor muscle during the execution of the oscillating trajectory plotted in Fig 6. The original SEMG recording (Fig.7a), its rectified waveform (Fig.7b), its envelope as calculated with a Savitzky-Golay filter (Fig.7c) and the corresponding velocity profile of the end-effector (Fig.7d) are successively presented. A comparative example is given in figures 7c and 7d where one can see the synchronization between the contraction of the agonist muscle, as represented by a burst, and the execution of an elementary stroke in a given direction of movement as well as the synchronization between the relaxation phase of this muscle and the return in the opposite direction, achieved by an antagonist muscle. In this experiment, the kinematic information of velocity is not used in the modeling of the envelope by a sum of lognormals. Fig. 8.a. illustrates the best fit of the envelope by a superimposition of ten time-shifted lognormals. One can thus deduce that the contribution of the digitorum profundus flexor muscle for the accomplishment of this specific complex movement corresponds to ten successive contractions occurring at specific instants. Fig. 8.b illustrates the corresponding activation periods, respectively circumscribed by $t_{onset}$ and $MT$ (calculated from Eq. 3 and 4) and, Fig. 8.c depicts the sequence of the command occurrences $\{t_{onset}\}_{i=1,...,10}$. As one can see, the oscillating movement is done by contracting the muscle with a fixed frequency, i.e. the time interval between two successive commands is almost constant, leading to a linear regression curve of $t_{onset}$ vs. $i$ (Fig.8c). Furthermore, the muscle activity, associated with each individual movement, overlaps during the task (Fig.8b); which means that the relaxation phase of a muscle is not complete.

**Figure.7.** Illustration of the SEMG of the digitorum profundus flexor muscle as recorded during the handwriting oscillations. (a) Original SEMG records (b)
rectified SEMG (c) its envelope and (d) the velocity profile of the end-effector (the fingers grasping the pen).

**Figure. 8.** (a) Fitting of SEMG envelopes by a sum of ten lognormals (b) corresponding muscle activities: each horizontal segment represents the activation duration, (c) representation of the command occurrences ($t_0$) versus the lognormal sequence

### 4. Conclusion

In this paper, a new methodology for surface electromyographic signal processing has been developed. It uses the Delta-Lognormal model, as a mathematical tool from which the movement onset and its duration can be measured and exploited. This methodology offers an indirect and noninvasive way to measure the time occurrence of the input commands $t_0$, the movement onset $t_{\text{onset}}$ and the duration (MT) without using any arbitrary thresholds.

By exploiting the time occurrence $t_0$ as the time-origin to compute the mean SEMG signals, the resulting envelope has a better signal to noise ratio, it encompasses less ripples and its pattern converges toward the asymmetric lognormal profile. Even in absence of kinematic information, the time schedule of a muscle activation can thus be estimated from a sequence of lognormal SEMG envelopes. The whole paradigm provides a new window to study human movements and a new scheme to control artificial muscles. Indeed, it is expected that in the long run, this method, that avoids arbitrary thresholds, will be used to decode the recruitment time schedule of different muscles involved in the control of skilled movement such as handwriting and thereby the construction of noninvasive signals from SEMG bio-signals, to eventually control anthropomorphic robots, prosthetic arms or exoskeleton systems.

### Acknowledgements

This work was supported by NSERC grant RGPIN-915 to Réjean Plamondon

### References


